Forecasting the long memory properties in volatility: Evidence from Korean and Australian futures markets

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Abstract

Accurate forecasting volatility is a matter of considerable interest in financial volatility research, particularly in studies of portfolio allocation, option pricing, and risk management. This article investigates/compares the ability to conduct one-day-ahead volatility forecasts in Korean and Australian index futures markets utilizing three volatility models, including GARCH, IGARCH, and FIGARCH. The FIGARCH model is more adequately equipped to capture the long memory property than are the GARCH and IGARCH models. Additionally, the FIGARCH model provides superior performance in one-day-ahead volatility forecasts. The results provided in this paper show that the FIGARCH model should prove useful in forecasting the long memory property in index futures markets.

Keywords: Forecasting volatility; long memory; FIGARCH; KOSPI 200 futures; SPI futures

JEL Classifications: C32; C52; E37;G13

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1. Introduction

Over the past two decades, the forecasting ability of conditional volatility models is a matter of considerable interest to financial researchers and practitioners, as volatility can be employed in the measurement of risk. Many studies addressing forecasting volatility stylized factors have focused on underlying stock markets via the use of popular generalized autoregressive conditional heteroskedasticity (GARCH) models (see Poon and Granger, 2003, for an excellent survey).

By way of contrast, the topic of forecasting volatility is a relatively new genre in index futures markets (Hourvouliades, 2007; Kung and Yu, 2008; Martin, 2002; Noh and Kim, 2006; Vipul and Jacob, 2007). Index futures contracts have undoubtedly been one of the most successful instruments in the recent financial market environment. The most crucial role of index futures contracts involves their functions as a mechanism by which risks and volatility in the underlying stock market can be managed. Investors and financial market participants can hedge against adverse short-term price movements via arbitrage trading, through the linked trading of stocks in both the spot and futures markets. Nevertheless, they may still experience some long-term market risks, and thus may require a more accurate method of forecasting volatility in index futures markets.

Recently, financial economists have paid a great deal of attention to persistence or long memory in the volatility of futures contracts (Dark, 2004; Tang and Sheih, 2006). "Long memory" means that shocks to conditional variance die at a hyperbolic rate, which is slower than the exponential rate of decay associated with shocks in the "short memory" GARCH models (Baillie, 1996). Such a long memory feature is a crucial component for market risk management, investment portfolios, and the pricing of derivative securities, as its presence reflects the predictability of futures volatility. Furthermore, long memory fractionally integrated GARCH (FIGARCH) models tend to provide more accurate out-of-sample forecasts than do the stationary GARCH and non-stationary IGARCH models (Lux and Kaizoji, 2007; Vilasuso, 2002).

The principal objective of this paper was to discover the best forecasting ability model in the volatility of two futures markets, namely the KOSPI 200 futures of Korean Exchange (KRX) and the SPI futures of the Sydney Futures Exchange (SFE). Taking into consideration the long memory property that characterizes futures markets, we have employed the GARCH, IGARCH, and FIGARCH models, and have evaluated the performance of their one-day-ahead forecasts using a wide array of forecasting error statistics. Our analysis provides us with insights into persistence and a good forecasting model in the volatility of futures markets.

The remainder of this paper is organized as follows. Section 2 discusses the FIGARCH model framework and presents the forecasting error statistics. Section 3 provides the statistical characteristics of the sample data and the estimation results. The final section, Section 4, contains some concluding remarks.

2. Model framework

2.1. FIGARCH model

In accordance with the work of Engle (1982), consider the time series y_t and the associated prediction error $\varepsilon_t = y_t - E_{t-1}[y_t]$, in which $E_{t-1}[\cdot]$ is the expectation of the conditional mean on the information set at time $t-1$. The standard GARCH model of Bollerslev (1986) is as follows:

$$\varepsilon_t = z_t \sigma_t, \; z_t \sim N(0,1), \tag{1}$$

$$\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2, \tag{2}$$

where $\omega > 0$, L denotes the lag or backshift operator, and $\alpha(L) \equiv \alpha_1 L + \alpha_2 L^2 + \cdots + \alpha_q L^q$, and $\beta(L) \equiv \beta_1 L + \beta_2 L^2 + \cdots + \beta_p L^p$. Assuming that $\alpha_i, \beta_i \geq 0$ for all i, the GARCH(p,q) model in Equation (2) can be rewritten in the form of an ARMA$(\max\{p,q\},q)$ model:

$$\phi(L)\varepsilon_t^2 = \omega + [1-\beta(L)]\nu_t, \tag{3}$$

where $\nu_t \equiv \varepsilon_t^2 - \sigma_t^2$ and $\phi(L) = [1-\alpha(L)-\beta(L)]$. The $\{\nu_t\}$ process, which is interpreted as innovations for the conditional variance, has a zero mean, and is serially uncorrelated. Assuming that all the roots of $\phi(L)$ and $[1-\beta(L)]$ lie outside of the unit root circle, the covariance stationary GARCH model is a short memory model, because a volatility shock decays at a rapid geometric rate. On the other hand, when the autoregressive polynomial $[1-\alpha(L)-\beta(L)]$ has a unit root, then the GARCH(p,q) process has a unit root in conditional variance. The corresponding IGARCH model of Engle and Bollerslev (1986) is given as follows:

$$\phi(L)(1-L)\varepsilon_t^2 = \omega + [1-\beta(L)]\nu_t. \tag{4}$$

However, the IGARCH model does not allow for modeling long memory in the volatility process, as volatility shocks in the IGARCH model never die out. That is, the IGARCH model is characterized by infinite memory. In order to overcome this problem, the FIGARCH model of Baillie, Bollerslev, and Mikkelsen (1996) can be obtained by replacing the difference operator in Equation (4) with the fractional differencing operator. The FIGARCH(p,d,q) model is given as follows:

$$\phi(L)(1-L)^d \varepsilon_t^2 = \omega + [1-\beta(L)]\nu_t, \tag{5}$$

where $0 \le d \le 1$ is the fractional difference parameter. The FIGARCH model provides greater flexibility for the modeling of the conditional variance, as it accommodates the covariance stationary GARCH model when $d = 0$, and the IGARCH model when $d = 1$, in special cases. For the FIGARCH model in Equation (5), the persistence of shocks to the conditional variance or the degree of long memory is measured by the fractional differencing parameter, d. Thus, the attraction of the FIGARCH model is that, for $0 < d < 1$, it is sufficiently flexible to allow for an intermediate range of persistence.

The parameters of the FIGARCH model can be estimated via non-linear optimization procedures in order to maximize the logarithm of the Gaussian likelihood function. Under the assumption that the random variable $z_t \sim N(0,1)$, the log-likelihood of Gaussian or normal distribution (L_{Norm}) can be expressed as follows:

$$L_{Norm} = -\frac{1}{2}\sum_{t=1}^{T}\left[\ln(2\pi) + \ln(\sigma_t^2) + z_t^2\right], \tag{6}$$

in which T is the number of observations. The estimation procedure of the FIGARCH model requires a minimum number of observations. This minimum number is associated with the truncation order of the fractional differencing operator $(1-L)^d$. In accordance with the standard procedure in the relevant literature, the truncation order of the infinite $(1-L)^d$ is set to 1,000 lags, as follows:

$$(1-L)^d = \sum_{k=0}^{1000} \frac{\Gamma(k-d)}{\Gamma(k+1)\Gamma(-d)} L^d . \tag{7}$$

2.2. Forecasting evaluation

In accordance with the relevant literature (Brailsford and Faff, 1996; Brooks and Persand, 2003; Degiannakis, 2004), daily *ex post* volatility (variance) is measured by the squared returns as follows:

$$\sigma_t^2 = r_t^2 \tag{8}$$

At time period t, the one-day ahead forecasting is calculated by the above three models which is estimated with one year of day trading data, for a total of 250 observations. The estimation period is then rolled forward via the addition of one new day and the dropping of the most distant day. In this fashion, the sample size utilized in the estimation of the models remains at a fixed length (2646 observations for the KOSPI 200 futures; 2452 observations for the SPI futures) and the forecasts do not overlap.

In order to measure forecast accuracy, we calculate the root mean squared errors ($RMSE$), the heteroskedasticity-adjusted RMSE ($HRMSE$) and the logarithmic loss errors (LL) of the volatility forecasts, as follows:

$$RMSE = \frac{1}{250}\sum_{i=1}^{250}\left[\left(\sigma_{f,t}^2 - \sigma_{a,t}^2\right)^2\right]^{1/2}, \tag{9}$$

$$HRMSE = \frac{1}{250}\sum_{i=1}^{250}\left[\left(1-\frac{\sigma_{f,t}^2}{\sigma_{a,t}^2}\right)^2\right]^{1/2}, \tag{10}$$

$$LL = \frac{1}{250}\sum_{i=1}^{250}\left[\ln\left(\frac{\sigma_{f,t}^2}{\sigma_{a,t}^2}\right)\right] \tag{11}$$

in which T is the number of forecast data points, and $\sigma_{f,t}^2$ denotes the volatility forecast for day t, whereas $\sigma_{a,t}^2$ signifies actual volatility on day t. Smaller forecasting error statistics reflect the superior forecasting ability of a given model.

Although the above statistics of forecast errors are useful for the comparison of estimated models, they do not provide statistical tests of the difference between the two models. Rather than comparing the forecasting error statistics of different forecasting models, it is important to determine whether any reductions in forecasting errors are statistically significant.

For this reason, Diebold and Mariano (1995) developed a test of forecast accuracy for two sets of forecasts. Having generated n, h-steps-ahead forecasts from different forecasting models, the forecaster has two sets of forecast errors $e_{1,t}$ and $e_{2,t}$, in which $t = 1,2,\ldots,n$. Using $g(e_{1,t})$ as a function of the forecasting errors, the hypothesis of equal forecast accuracy can be represented as $E[d_t] = 0$, in which $d_t = g(e_{1,t}) - g(e_{2,t})$ and E is the expectation operator. The mean of the difference between the forecasting errors $\bar{d} = n^{-1}\sum_{t=1}^{n} d_t$ has an approximate asymptotic variance of

$$V\left(\bar{d}\right) \approx n^{-1}\left[\gamma_0 + 2\sum_{k=1}^{h-1}\gamma_k\right], \tag{12}$$

where γ_k is k-th autocovariance of d_t, which can be estimated as:

$$\hat{\gamma} = n^{-1}\sum_{t=k+1}^{n}\left(d_t - \bar{d}\right)\left(d_{t-k} - \bar{d}\right). \tag{13}$$

The Diebold and Mariano (1995) test statistic for testing the null hypothesis of equal forecast accuracy is :

$$DM = \left[\hat{V}\left(\bar{d}\right)\right]^{-1/2}\bar{d}, \tag{14}$$

in which DM has an asymptotic standard normal distribution under the null hypothesis. In this paper, the DM test is calculated from a loss differential on the basis of the $RMSE$, $HRMSE$ and LL of different forecasting models.

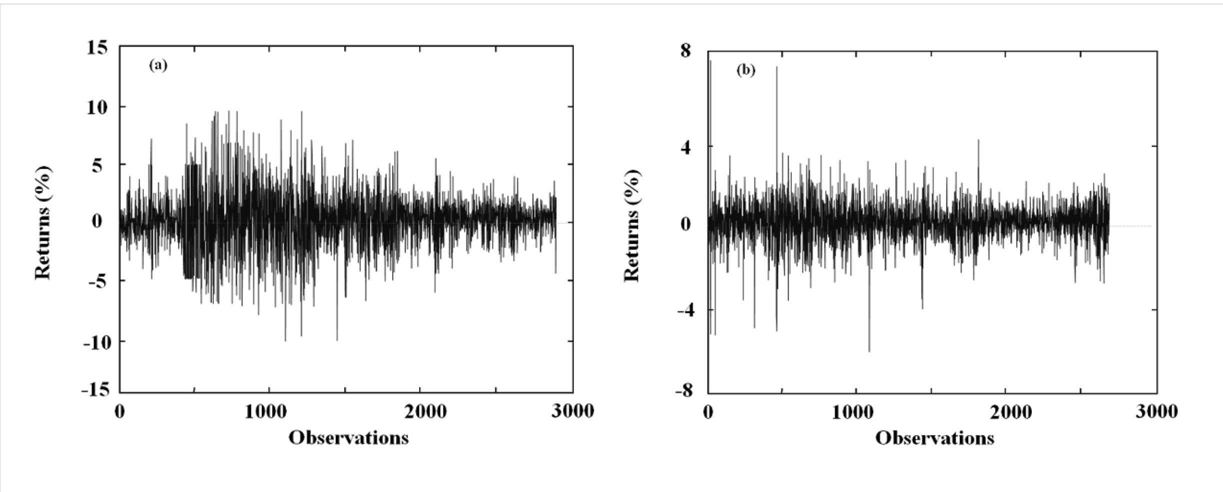
3. Empirical results

3.1. Data

The sample data in this study consists of the daily stock index closing prices in the two index futures contracts: the KOSPI 200 futures and the SPI futures. First, the KOSPI 200 futures contract is predicated on the underlying KOSPI 200, which is a capitalization-weighted index of the stock prices for 200 companies listed on the KRX. The daily sample data of the KOSPI 200 futures contract encompasses the period between May 3, 1996 and July 31, 2007, obtained from the KRX database.

Second, the SPI futures contract is a major speculative and hedging instrument written on the All Ordinaries Index, which in turn represents the top 300 or so market capitalized stocks traded on the Australian Stock Exchange (ASX). The daily sample data of the SPI futures contract commences on January 2, 1996 to September 5, 2006, and was sourced from the Datastream database.

Figure 1. The dynamics of daily sample returns: (a) KOSPI 200 futures, (b) SPI futures



All sample prices are converted into daily nominal percentage return series for futures prices, i.e., $r_t = 100\ln(P_t/P_{t-1})$ for $t = 1,2,\ldots,T$, where r_t is the return for futures prices at time t, P_t is the current price, and P_{t-1} is the previous day's price. Figure 2 plots the dynamics of returns for both of the futures returns. Descriptive statistics for the return series of futures prices are summarized in Table 1. All sample returns evidence a similar pattern of results. The sample mean of returns is quite small, and the corresponding variance of returns is significantly higher. Both the skewness and kurtosis statistics in the table show that the return distribution is not normally distributed. Likewise, the Jarque-Bera (J-B) statistics also reject the null hypothesis of normality in the distribution of the sample return series.

Table 1. Descriptive statistics for sample futures price returns

Series	KOSPI 200 futures	SPI futures
Number of observations	2896	2702
Mean (%)	0.027	0.030
Standard deviation (%)	2.340	0.918
Minimum	-10.53	-6.053
Maximum	9.531	7.625
Skewness	-0.002	-0.084
Kurtosis	4.894	8.994
Jarque-Bera	432.81 [0.000]	4048.61 [0.000]
$Q_S(24)$	2205.9 [0.000]	344.29 [0.000]

Notes: The Jarque-Bera statistic tests for the null hypothesis of normality in sample returns distribution. The Box-Pierce statistic $Q_S(24)$ for the squared return series for up to 24th order serial correlation. P-values are given in baskets.

We also assess the null hypothesis of a white-noise process for sample returns employing the Box-Pierce test statistics for the squared returns $Q_s(24)$. According to the calculated values of the $Q_s(24)$ statistics shown in Table 1, the null hypothesis of no serial correlation is rejected. Thus, significant evidence exists for serial dependence in the squared returns.

Prior to testing for the long memory property in volatility, both of the sample return series are subjected to two unit root tests--PP (Phillips-Peron) and KPSS (Kwiatkowski, Phillips, Schmidt, and Shin) tests--in order to determine whether stationarity or integration should be considered for each set of daily data. These tests differ with regard to the null hypothesis. The null hypothesis of the PP test asserts that a time series contains a unit root, $I(1)$ process, while the KPSS test has the null hypothesis of stationarity, $I(0)$ process.

Table 2. Unit root tests for sample returns

	$H_0 : I(1)$		$H_0 : I(0)$	
	$Z(t_\mu)$	$Z(t_\tau)$	$\hat{\eta}_\mu$	$\hat{\eta}_\tau$
KOSPI 200 futures	-52.16(20)***	-52.21(22)***	0.283(20)	0.047(21)
SPI futures	-57.32(18)***	-57.31(18)***	0.100(20)	0.063(20)

Notes: (1) $Z(t_\mu)$ and $Z(t_\tau)$are the Phillips-Perron adjusted t-statistics of the lagged dependent variable in a regression with intercept only, and intercept and time trend included, respectively. Mackinnon's 1% critical values for $Z(t_\mu)$ and $Z(t_\tau)$ are -3.44 and 3.96. (2) $\hat{\eta}_\mu$ and $\hat{\eta}_\tau$ are the KPSS test statistics based on residuals from regression with an intercept only, and intercept and time trend, respectively. The critical values for $\hat{\eta}_\mu$ and $\hat{\eta}_\tau$ are 0.739 and 0.216 at the 1% significance level. Numbers in parentheses represent the lag of periods of the tests. *** indicates rejection at the 1% significance level.

The empirical results of the unit root tests for all sample returns are provided in Table 2. For the PP test, the large negative values observed in all cases support the rejection of the null hypothesis of a unit root at a significance level of 1%, whereas the statistics of the KPSS test show that all return series are insufficient to reject the null hypothesis of stationarity, thereby implying that they are stationary processes. Thus, the futures return series are stationary and are appropriate for subsequent tests in this study.

Table 3. Estimation results from Lo's R/S analysis

	Returns	Actual volatility (squared returns)
KOSPI 200 futures	1.115 [0.700]	3.551 [0.005]**
SPI futures	1.107 [0.700]	2.000 [0.025]**

Note: The critical value of Lo's modified R/S analysis is 2.098 at the 1% significance level. P-values are given in baskets. ** indicates rejection at the 5% significance level.

The results of Lo's R/S test statistic for daily returns and squared returns are provided in Table 3.[1] With regard to the returns, the value of the modified R/S statistic supports the null hypothesis of short memory, thereby implying little evidence of long memory on the level of returns. However, the volatility shows strong evidence of long memory, thereby indicating that its autocorrelation function decays at a hyperbolic rate, rather than an exponential rate, over the longer lags.

3.2. Long memory of futures volatility

In this section, we proceed with the estimation of GARCH class models described by Equations (1) ~ (5) in order to capture the long memory property in the volatility of the two futures returns.[2] This section also compares the performance of the GARCH$(1,1)$, IGARCH$(1,1)$, and FIGARCH$(1,1)$ models with regard to the capture of the long memory property in volatility.

Table 4 reports the estimation results of these models. This table also provides a set of diagnostic tests: (1) The Box-Pierce Q_s statistic tests the $i.i.d.$ series of squared standardized

[1] To save space, Lo's modified R/S analysis specifications are not presented here. See Lo (1991) for more details.
[2] The estimation results in this study have been produced using the quasi-maximum likelihood estimation method of Bollerslev and Wooldridge (1992).

residuals. If the conditional variance equations are specified correctly, then the Q_s statistic should support the null hypothesis of the $i.i.d.$ series. (2) The lowest values of the Schwarz-Bayesian information criterion (SIC) indicate the best model amongst the GARCH, IGARCH, and FIGARCH models. (3) The LM ARCH statistic described by Engle (1982) is utilized to test for the presence of remaining ARCH effects in the residuals. The $\text{ARCH}(10)$ statistic tests the joint significance of lagged squared residuals up to the 5th order. (4) The likelihood ratio statistic (LR) tests for the linear constraints $d=0$ (GARCH model) and $d=1$ (IGARCH model).

Table 4. Estimation results of the FIGARCH model

Series	**KOSPI 200 futures**			**SPI futures**		
	GARCH	IGARCH	FIGARCH	GARCH	IGARCH	FIGARCH
μ	0.052 (0.035)	0.053 (0.035)	0.058 (0.035)*	0.050 (0.016)***	0.051 (0.017)***	0.049 (0.016)***
ω	0.032 (0.012)***	0.025 (0.010)**	0.062 (0.035)*	0.017 (0.011)*	0.007 (0.005)	0.190 (0.057)***
ϕ_1	0.074 (0.012)***	0.077 (0.013)***	0.146 (0.044)***	0.075 (0.026)***	0.077 (0.028)***	0.511 (0.214)**
β_1	0.922 (0.012)***	1-0.077	0.612 (0.061)***	0.906 (0.034)***	1-0.077	0.389 (0.233)*
d	-	-	0.484 (0.061)***	-	-	0.221 (0.036)***
$\ln(L)$	-5730.46	-5730.97	-5717.51	-3090.17	-3095.38	-3068.90
SIC	4.343323	4.340733	4.336514	2.533262	2.534329	2.519092
$Q_s(24)$	21.15 [0.511]	21.86 [0.468]	13.15 [0.929]	32.70 [0.066]	36.57 [0.026]	13.87 [0.906]
ARCH(5)	1.389 [0.223]	1.383 [0.227]	0.613 [0.690]	4.136 [0.000]	4.410 [0.000]	0.969 [0.435]
LR test	25.90 [0.000]	26.92 [0.000]	-	42.54 [0.000]	52.96 [0.000]	-

Notes: Standard errors are in parentheses below corresponding parameter estimates. $\ln(L)$ is the value of maximized Gaussian log likelihood and ARCH (5) represents the t-statistics of ARCH test statistic with lags 5. The LR test statistics, $LR = 2\cdot[ML_u - ML_r]$, where ML_u and ML_r denote the maximum log-likelihood values of the unrestricted FIGARCH model and restricted GARCH and IGARCH models, respectively. The numbers in brackets are p-values. *, ** and *** indicate rejection at the 10%, 5% and 1% significance levels, respectively.

As is shown in the estimation results of the $\text{GARCH}(1,1)$ model shown in Table 4, the estimated values of the persistence coefficient ($\beta_1 + \phi_1$) using both futures return series are quite close to unity, a fact which favors the $\text{IGARCH}(1,1)$ specification. As the $\text{IGARCH}(1,1)$ model nests the $\text{GARCH}(1,1)$ model, the estimates of the $\text{IGARCH}(1,1)$ model are quite similar to those of the $\text{GARCH}(1,1)$ model. Consequently, there is minimal difference between the $\text{GARCH}(1,1)$ model and the $\text{IGARCH}(1,1)$ model for both of the futures prices.

According to the lowest values of both the information criteria and the insignificance of $Q_s(24)$, $\text{ARCH}(5)$ at the bottom of Table 4, the $\text{FIGARCH}(1,1)$ model appears to be superior to the $\text{GARCH}(1,1)$ and $\text{IGARCH}(1,1)$ models in the description of volatility persistence for both of the futures returns. For example, the estimates of the long memory parameter d (0.484 for the KOSPI 200 futures; 0.221 for the SPI futures) reject the null hypotheses of the GARCH model$(d = 0)$ and the IGARCH model$(d = 1)$, and the LR statistics also reject the null hypothesis. Thus, the $\text{FIGARCH}(1, d, 1)$ model most accurately represents the long memory property in the conditional variance of both of the futures markets.

Consequently, this finding implies that volatility is highly persistent, and also that volatility models including GARCH and IGARCH provide misleading results in the estimation and forecasting of futures price volatility. Furthermore, the presence of long memory conflicts directly with the validity of the weak form efficiency of futures markets.

3.3. In-sample error statistics

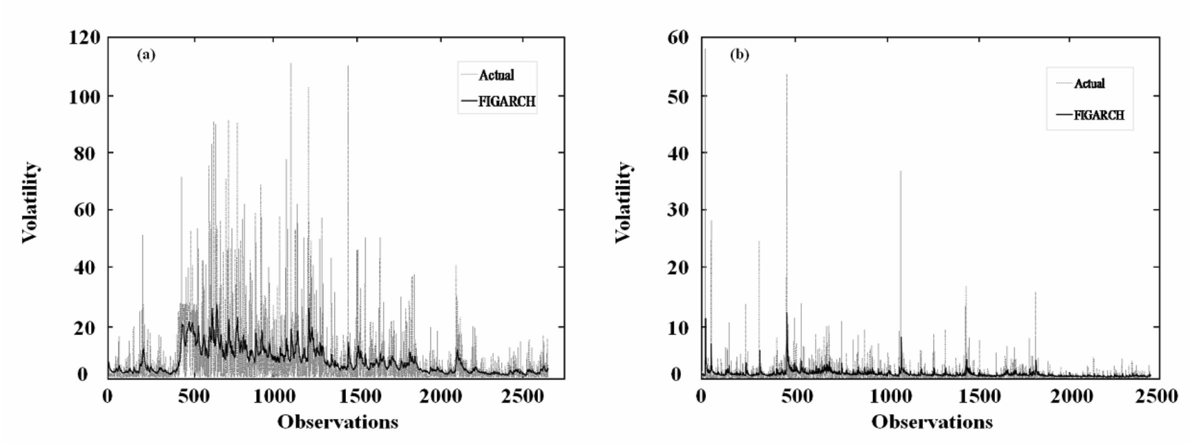
The in-sample error statistics for the KOSPI 200 futures and SPI futures contracts are summarized in Table 5. These statistics are employed as model selection criteria. Due to the lowest values of all error statistics, the FIGARCH model provides the most accurate forecasts in in-sample analysis. In addition, the *DM* test verifies that the FIGARCH model outperforms other models (GARCH and IGARCH models) to assess the long memory property in the in-sample period. According to Figure 2, which plots the actual volatility and the volatility or conditional variance of the FIGARCH model, the FIGARCH model very closely tracks the actual volatility.

Table 5. In-sample error statistics

Series	Models	*RMSE*	*DM*	*HRMSE*	*DM*	*LL*	*DM*
KOSPI 200 futures	FIGARCH	**5.818**	-	**50.47**	-	**1.252**	-
	IGARCH	5.946	-6.19**	53.11	-4.26**	1.292	-5.36**
	GARCH	5.881	-3.15**	52.05	-2.93**	1.275	-9.99**
SPI futures	FIGARCH	**0.911**	-	**34.15**	-	**1.218**	-
	IGARCH	0.971	-7.46**	37.21	-4.81**	1.287	-15.09**
	GARCH	0.931	-3.09**	35.44	-2.96**	1.244	-7.11**

Note: The values in bold refer to the lowest for the *RMSE* , *HRMSE* and *LL* error statistics. The *DM* test statistic is used to evaluate the null hypothesis that the forecasting accuracy of the FIGARCH model is the same as either the GARCH or IGARCH model. ** indicates that the null hypothesis of the *DM* test is rejected at the 5% significance level.

Figure 2. The conditional variance of FIGARCH model: (a) KOSPI 200 futures, (b) SPI futures



3.4. Forecasting the volatility of futures returns

In the preceding sections, although the FIGARCH model appears to fit the futures price data well, a crucial question remains: does this model do as good a job in volatility predictions as do the other models? Thus, this section evaluates one-day-ahead volatility forecasts and compares the accuracy of the volatility forecasts.

Figure 3 illustrates the one-day-ahead volatility forecasts estimated from the GARCH $(1,1)$, IGARCH $(1,1)$, and FIGARCH $(1,1)$ models. Although the one-day-ahead volatility forecasts from the three models are quite similar to each other, both sub-figures demonstrate that the volatility forecasts from the FIGARCH model tend to follow the actual volatility quite closely. In particular, the volatility forecast of the FIGARCH model evidences more sensitive peaks and curves corresponding to the movement of actual volatility than do other models.

Table 6 summarizes the results of the one-day-ahead volatility forecast error statistics. Three error statistics support the notion that the FIGARCH model, which allows for long memory in the conditional variance, is superior to the GARCH and IGARCH models. In addition, the values of the DM test statistics are negative, and significantly reject the null hypothesis, thereby implying that the FIGARCH model outperforms the other forecasting models. As a result, the long memory FIGARCH model generates more accurate one-day-ahead volatility forecasts than do the other short memory models.

Figure 3. Comparison the one-day-ahead volatility forecasts from the GARCH$(1,1)$, IGARCH$(1,1)$ and FIGARCH$(1,1)$ models: (a) KOSPI 200 futures, (b) SPI futures

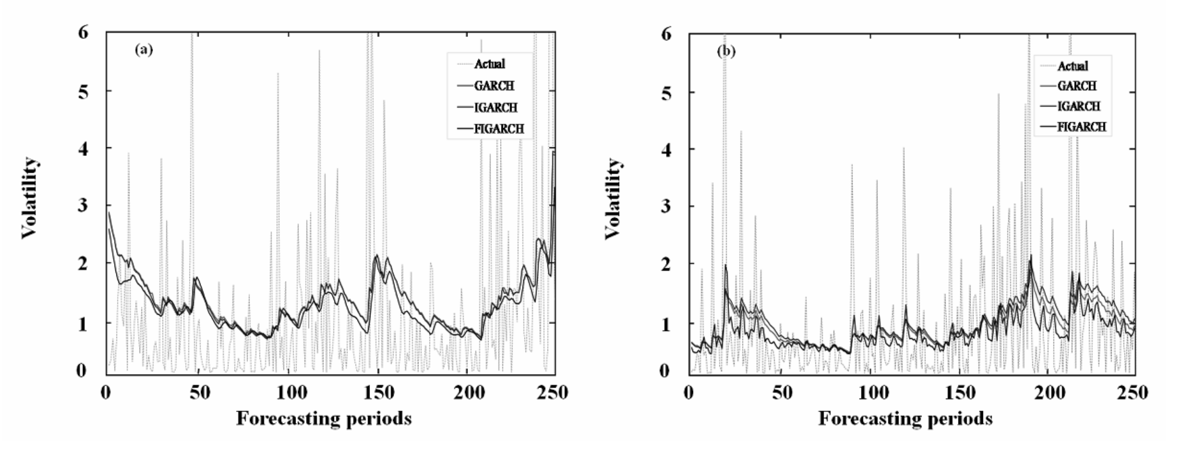


Table 6. One-day-ahead volatility forecasts

Series	Models	*RMSE*	*DM*	*HRMSE*	*DM*	*LL*	*DM*
KOSPI 200 futures	FIGARCH	**1.159**	-	**69.19**	-	**1.447**	-
	IGARCH	1.205	-3.57**	75.32	-3.15**	1.535	-12.94**
	GARCH	1.214	-4.24**	76.92	-2.70**	1.552	-16.41**
SPI futures	FIGARCH	**0.816**	-	**280.60**	-	**1.275**	
	IGARCH	0.877	-4.10**	350.63	-2.24**	1.471	-17.02**
	GARCH	0.849	-3.04**	335.63	-2.21**	1.410	-13.99**

Note: The values in bold refer to the lowest for the *RMSE* , *HRMSE* and *LL* error statistics. The *DM* test statistic is used to evaluate the null hypothesis that the forecasting accuracy of the FIGARCH model is the same as either the GARCH or IGARCH model. ** indicates that the null hypothesis of the *DM* test is rejected at the 5% significance level.

4. Conclusions

In this article, we have attempted to delineate a good volatility model with the ability to forecast and identify volatility stylized facts, and in particular volatility persistence or long memory, in Korean and Australian futures markets. In this context, we assess the long memory property in the volatility of futures contracts, using three conditional volatility models--namely the GARCH, IGARCH, and FIGARCH models. The FIGARCH model is better equipped to capture the long memory property than are the GARCH and IGARCH models. More importantly, the FIGARCH model provides superior performance in one-day-ahead volatility forecasts. Thus, we conclude that the FIGARCH model should prove useful to financial economists, policy markers, and financial analysts who are interested in modeling and forecasting the dynamics of futures volatility.

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